

Application of EEMD-ICA algorithm to EMG signals measured in laryngeal muscles

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Abstract—This paper describes the application of EEMD-ICA algorithms on electromyographic signals measured in laryngeal muscles. The method was used for the separation of single-channel data into independent components. During the speech, there was a transcranial magnetic stimulation of the motor cortex area of the brain for speech production i.e. primary motor region of the laryngeal muscles (M1) and Broca's region. Manifestation of magnetic stimulation of those cortex areas and speech itself is recorded in the form of electromyographic signals in laryngeal muscles. The measured signals are a mixture of two different sources: natural stimulus (speech) and the effect of electromagnetic stimulation depending on the area of the speech cortex that is stimulated. This research demonstrated that using EEMD-ICA method, signal which is a mixture of speech and the effect of electromagnetic stimulation to specific areas of the speech cortex, can be successfully separated to the original components. The results were obtained using Matlab. The impact of magnetic stimulation to brain regions is detected and isolated from the laryngeal muscle signal.

Keywords—*Independent Component Analysis (ICA); Ensemble Empirical Mode Decomposition (EEMD); transcranial magnetic stimulation; signal processing*

I. INTRODUCTION

Nowadays, neurosurgeons must take into account various regions in the brain. During the removal of tumors their task is to perform the surgery with lowest possible deficit. Important information neurosurgeons can get in preparation of operations and during the operations regarding the patient's regions found in the brain.

Motor cortex areas of the brain critical for creating speech are Broca's region (opercular part) and the primary motor cortex (M1) for the muscles of the face, mouth, pharynx and larynx. Broca's region has an important role in motor control of speech and sends the coded information to the M1 region for execution of articulatory movements. From M₁ information is sent through corticobulbar tract toward the laryngeal muscles, face, mouth and throat [1]. Methodology of intraoperative stimulation and registration of neurophysiological markers for M1 area of the larynx muscles and opercular part of Broca's region was recently developed [2] Neurophysiological markers of specific areas of motor cortex for speech are registered in the laryngeal muscles. In order to develop a methodology for preoperative mapping of Broca's region and M1 for laryngeal muscles during a specific

speech task (naming visually presented objects on a computer screen), transcranial magnetic stimulation is applied to these regions respectively. Manifestation of the magnetic stimulation of the speech cortex area is speech recorded in the form of electromyographic (EMG) signal in the laryngeal muscles. Measured signal is a mixture of two different sources: natural excitation (speech) and the effect of magnetic stimulation on those areas EEMD-ICA algorithm was successfully applied to separate the recorded signals to independent components.

In recent years, scientists from Katholieke Universiteit Leuven applied method EEMD-ICA for signal separation. The above-mentioned method was applied for the removal of artifacts in EMG signals and gave better results when compared with other methods [7] [8].

In this work, for the first time, the signals measured in the muscle of the larynx using EMD-ICA algorithms are separated into independent components.

The paper is organized as follows. In Section II, all the methods and algorithms used in this paper are shortly described. Chapter III provides an overview of the results and comment. A short conclusion summarizes in chapter IV.

II. METHOD

A Method of stimulating the motor cortex area of the brain for speech and registration of responses in laryngeal muscle.

Previously prepared magnetic resonance images (MRI) of the participants are integrated in the navigational transcranial magnetic stimulator with three-dimensional navigation system for displaying the brain (nTMS-NBS) (Helsinki, Finland). NBS system provides accurate and detailed map of eloquent regions of the cortex, indicating it on a standard MRI image. Using NBS, combined with stereotactic MRI image of brain and a series of magnetic stimuli allows accurate non-invasive excitation of the cortex. Stimulation was performed with a short series of high-frequency stimuli: four stimuli packages with five stimuli within a single package, 6 ms interstimulus interval and 250 ms of time between the stimuli packages. To record the response from laryngeal muscles, hooked-wire electrodes were used, each electrode having a diameter of 76 μm , coated with Teflon. Stimulation was applied while the participants were engaged in the task of naming objects / images displayed on a computer screen (LG 22 "LCD" with 1920 x 1080 resolution) using the program Presentation

(Neurobehavioral Systems, Albany, CA). Images are black and white and are shown on white background while in the right corner of the monitor is a sensor which tracks beginning and ending of displaying the object. Images are presented for 3000 ms, followed by a black background in the duration of 2390 ms. Total time from beginning of displaying one image to beginning of displaying another image is 5390 ms. Program Presentation triggers beginning of stimulation 10-300 ms after the presentation of the object on a computer screen. Stimulated are two motor areas of the cortex for speech: M1 for laryngeal muscles and opercular part of Broca's region. EMG signal is recorded in the laryngeal muscle (cricothyroid muscle).

During stimulation of M1 signal, it takes 13.25 ± 1.38 ms for the signal to travel from the brain to the laryngeal muscles, and for Broca's region the signal is registered in 40.53 ± 4.66 ms after application of stimulation [3]. The muscles of the larynx are contracted and the electrical signals are registered during the speech, as well as the effect of magnetic stimulation of the individual areas of speech cortex. In order to detect and isolate the impact of magnetic stimulation to signal mixture it is necessary to apply the EEMD-ICA algorithm.

B Independent Component Analysis (ICA)

ICA is a method that separates independent components (reconstruction of the original signals) from a linear combination (mixture) of these signals with almost no information about the original signals. The procedure is based on the minimization of correlation and increasing the statistical independence of mixed signals. Starting from the following assumptions that there are n linearly mixed signals x_1, \dots, x_n arising from n independent components:

$$x_j = a_{j1}s_1 + a_{j2}s_2 + \dots + a_{jn}s_n \quad j = 1, \dots, n \quad (1)$$

It is assumed that all the mixed signals x_j and all independent signals (sources) are random variables. Time signals $x_j(t)$ represent the observation of a random variable x_j . Without loss of generality, we can assume that all the random variables in an equation have zero mean value. If the x denotes the vector containing the mixture of x_1, \dots, x_n , with the s vector containing the random variable s_1, \dots, s_n and with A matrix containing the coefficients a_{ij} , the expression (2) is obtained.

$$x = As \quad (2)$$

Equation (2) represents the ICA model. In the presented equations unknown are the sources s_{ij} which form the mixture and the mixing matrix A . Based on the known information about the mixed signals it is necessary to find a mixing matrix A and the independent components s_{ij} (sources) of signals. For successful use of ICA algorithms following conditions have to be satisfied:

- Sources that are forming mixed signals need to be statistically independent
- Sources must not have Gaussian distribution (except for one)
- It is possible to find a matrix W that is inverse to the matrix A . ($A^{-1} = W$)

The matrix of the original components is defined by the following expression:

$$s = Wx \quad (3)$$

In order to separate the mixed signals on the original (3) components it is needed to find a separation matrix W . It is not possible to pinpoint the original components so we seek the closest approximation. The central limit theorem of probability theory says that the distribution of sums of independent random variables tends to a Gaussian distribution. This fact is used in approximating the independent components. Component is approximated by minimizing the similarity of its distribution with Gaussian distribution because similarity is lowest if approximation corresponds to one of the independent components, while higher if it corresponds to the sum of two or more components. A large number of ICA algorithms were developed. On the signals in the laryngeal muscles FastICA algorithm was applied.

FastICA algorithm

FastICA algorithm performs separation of mixed signals to its original components based on non-Gaussianity. Properties of FastICA algorithm are as follows:

- 1.) Convergence is cubic (or at least squared). With this it differs from other ICA algorithms based on (stochastic) gradient descending methods where convergence is linear. Convergence is very fast.
- 2.) Algorithm is easy to use because there is no selection of coefficients for learning.
- 3.) Algorithm directly finds independent components of almost any non-Gaussian distribution using some of the functions to evaluate negentropy.
- 4) It is possible to affect the actual execution of the algorithm, which can be optimized. We can implement algorithms that are more resistant and / or have a minimum variance.
- 5). Independent components can be counted one by one.

The algorithm is computationally simple and requires little memory [4].

C Empirical Mode Decomposition (EMD)

Empirical decomposition method (EMD), is primarily developed for the purpose of processing non-stationary signals, and is based on the process of decomposition of the signals to a series of simpler eigenfunctions (Intrinsic Mode Function - IMF) with good mathematical behavior, and because of its properties is often highlighted as an effective and efficient method of decomposition of the signals. IMF is a function in which the number of zero crossings and extrema at most differ by one, and in which at all points the difference between the envelope maximum and envelope minimum equals zero. The process of separation of signal on IMF functions: First are identified all local extrema in the signal - maxima and minima. Then all the local maxima are connected by 'cubic spline' function which gives the upper envelope. By linking all of the local minima using the same functions, we get the lower

envelope. Upper and lower envelope together roughly cover the entire signal. Their mean value is marked with m_1 .

$$m_1(t) = (x_g(t) + x_d(t))/2 \quad (4)$$

where x_g is upper envelope (connects all maxima), and x_d lower envelope (connects all minima). The difference between the original signal $x(t)$ and the mean envelope m_1 is the first component h_1 .

$$h_1 = x(t) - m_1 \quad (5)$$

Ideally, h_1 should satisfy the definition of IMF function by the way it is formed that made this function symmetrical, and all its maxima positive and all minima negative. After applying this procedure (first iteration), even a small hump on a slope can become a local extremum. New extremum obtained this way can reveal the correct component that we lost in the first iteration. By repeating, this procedure can detect components of very small amplitude that appear within signal. In the next iteration, h_1 can be seen as a potential IMF. If we find that it does not meet the requirements that are put on the IMF function, then it is treated as a "new" signal and is reentered in the process of getting the IMF's.

$$h_{11} = h_1 - m_1 \quad (6)$$

By repeating the iterations k times as described above h_{1k} becomes IMF:

$$h_{1k} = h_{1(k-1)} - m_{1k} \quad (7)$$

$$c_1 = h_{1k} \quad (8)$$

After selecting all the IMF's the last signal (residue) remains which is either a constant or a monotonic function. The original signal can be obtained by summing all the IMF's and the residue [5].

One of the greatest disadvantages of the original EMD method is frequent occurrence of mode mixing. Mode mixing in the IMF manifests with amplitudes that are significantly different as well as occurrence of similar waveforms in neighboring IMF's. This problem is successfully solved by EEMD (Ensemble EMD).

D. Ensemble Empirical Mode Decomposition (EEMD)

EEMD algorithm defines the real IMF as the mean value of IMF's obtained from the ensemble of test signals, wherein the white noise of the finite amplitudes added to the test signal. Since for each test signal a different realization of white noise is added to the original signal, averaging IMF's through the ensemble of test signals will annul the presence of noise and will, as the ultimate result, remain only true IMF's of the original signal [6].

III. RESULTS

In this paper EEMD-ICA method is applied in such a way that the signals are divided into segments of 4000 samples. Inside 4000 samples every single word can fit in. At each one word

signal segment, EEMD method is applied first and the IMF functions are obtained. From 10 to 12 obtained IMF functions, only first five were used because it was determined that no further layering is necessary. Thus obtained IMF functions are used as input to the Fast-ICA algorithm. After applying FastICA algorithm, five independent components are obtained. For graphical presentation, only one estimated independent component has been chosen. Rectangular window areas are drawn in the places of expected stimulation response, as defined in study described in [3].

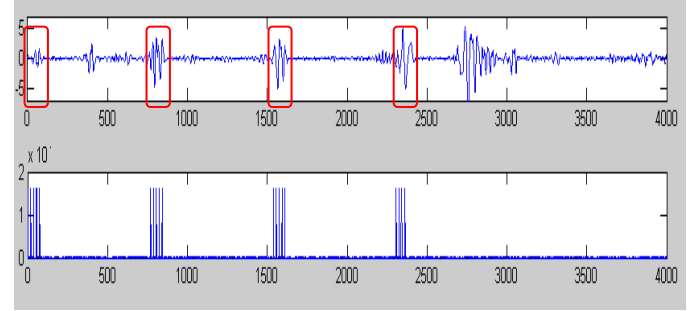


Figure 1a

The first part of Figure 1a shows the pronounced word during the stimulation of the region M1. The second part of the image shows the magnetic stimulation. The expected response in the larynx muscle occurs 13 ± 1.07 ms after stimulation. The figure shows that after each stimulus package, a response in the muscle in the larynx occurs short latency response (SLR). (The horizontal axis is the time in milliseconds, while the vertical axis shows the amplitude in mV.) The sampling frequency is 3000 Hz.

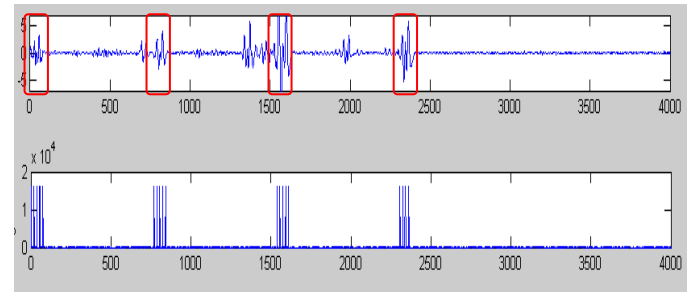


Figure 1b

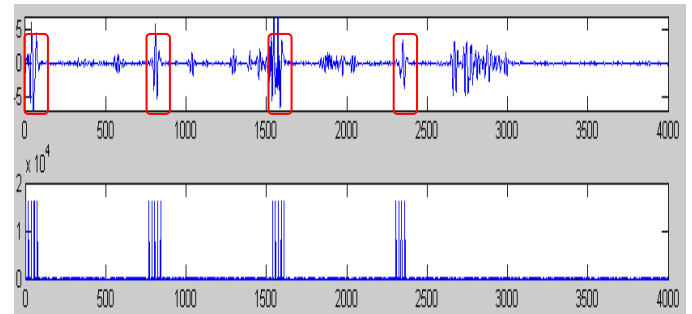


Figure 1c

Figures 1a-1c show signals during stimulation of M1 region of the brain. In each figure, there are two signals. The first is the one of five ICA independent components estimated from EEMD decomposition of the signal measured in the muscle of the larynx. Figure below is the signal of magnetic stimulation.

In Figures 2a-2c are (in the same way as for the region M1) displayed the signals when stimulation was executed on Broca's region. Effects of magnetic stimulation (markers) are manifested in the laryngeal muscles, and could be visible in rectangular areas drawn at expected places.

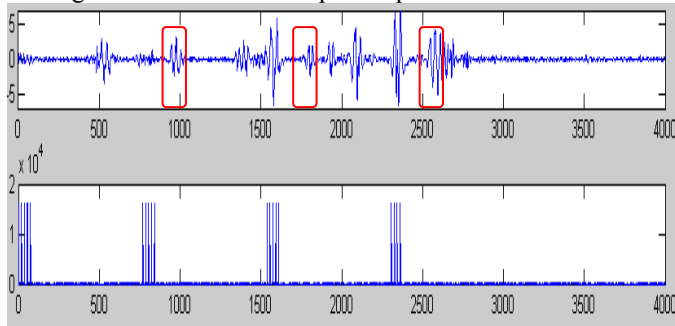


Figure 2a

The first part of Figure 2a shows the pronounced word during the stimulation of the Broca's region. The second part of the image shows the magnetic stimulation. The expected response in the larynx muscle occurs 44 ± 3.88 ms after stimulation. The figure shows that after each stimulus package, a response in the muscle in the larynx occurs long latency response (LLR). (The horizontal axis is the time in milliseconds, while the vertical axis shows the amplitude in mV.) The sampling frequency is 3000 Hz.

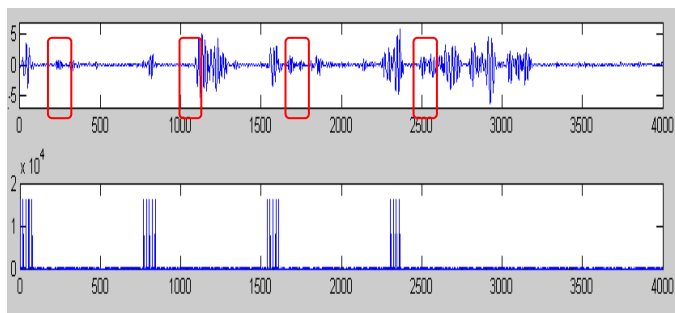


Figure 2b

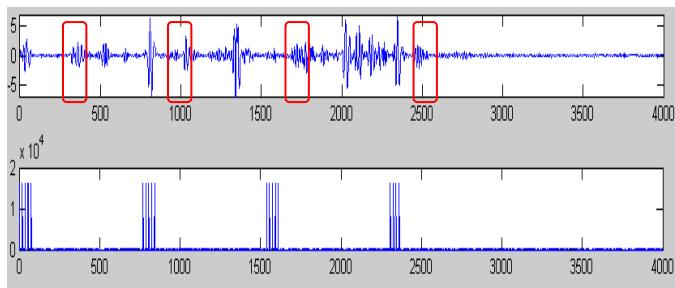


Figure 2c

IV. CONCLUSION

Magnetic stimulation was performed on both regions of the brain and for both regions manifestation of the impact of magnetic stimulation is visible in the muscle of the larynx.

Since the stimulation is performed by magnetic stimulation, which in contrast to electrical stimulation is not concentrated in one spot, and the fact that the two regions responsible for pronunciation (Broca's region and M1) are very close, sometimes it happens that stimulation simultaneously encompass both regions and manifestation of magnetic stimulation in the laryngeal muscles can be detected in time 13 ± 1.07 ms after stimulation indicating that the region M1 is stimulated, as well as in time of 44 ± 3.88 ms suggesting that Broca's region is stimulated.

Quantitative indicator, such as sum of squared amplitude, can explicitly determine whether there was stimulation, and if so, in which places it was performed. A certain amount of noise is present in the signals and further research is possible using the machine learning algorithms.

Well separated signals can have a practical application in preoperative mapping of motor areas of the cortex for speech, planning and execution of neurosurgical operations in order to preserve the motor areas of the cortex for speech and preventing postoperative deficits in speech.

REFERENCE

- [1] J. Espadaler, M. Rogić, V. Deletis, A. Leon, C. Quijada, G. Conesa: "Representation of cricothyroid muscles at the primary motor cortex (M1) in healthy subjects, mapped by navigated transcranial magnetic stimulation (nTMS)", Clin Neurophysiol. 123(11), pp. 2205-11, 2012
- [2] V. Deletis, I. Fernandez-Conejero, S. Ulkatan, M. Rogić, S.L. Carbo: "Methodology for intra-operative recording of the corticobulbar motor evoked potentials from cricothyroid muscles", Clin Neurophysiol. 122 (9), pp. 1883-1889, 2011
- [3] M. Rogić: "Contribution to the methodology of identification of neurophysiological markers in laryngeal muscles elicited by transcranial magnetic stimulation (TMS) of motor speech related cortical areas governor", PhD thesis, University of Split, School of medicine, May 2012.
- [4] A. Hyvarinen, E. Oja: "Independent component analysis: algorithms and applications", Neural Networks 13, pp. 411-430, 2000
- [5] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, et al., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis", Proc. R. Soc. Lond. A 454, pp. 903-995, 1998
- [6] Z. Wu, N. E. Huang, "Ensemble empirical mode decomposition: A noise-assisted data analysis method," Advances in Adaptive Data Analysis, vol. 1, no. 1, pp. 1-41, 2009
- [7] B. Mijović, M. De Vos, I. Gligorićević, J. Taelman, S. Van Huffel, "Source separation from single-channel recordings by combining empirical-mode decomposition and independent component analysis", IEEE Trans. Biomed. Eng., vol. 57, No. 9, pp. 2188-2196, 2010
- [8] B. Mijović, M. De Vos, I. Gligorićević, S. Van Huffel: "Combining EMD with ICA for Extracting Independent Sources from Single Channel and Two-Channel Data" 32nd Annual International Conference of the IEEE EMBS Buenos Aires, Argentina, August 31 - September 4, 2010